IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received March 18, 2016, accepted April 21, 2016, date of publication May 11, 2016, date of current version June 3, 2016.

Digital Object Identifier 10.1109/ACCESS.2016.2566958

A Distributed SON-Based User-Centric Backhaul Provisioning Scheme

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This work was supported by the U.K. Engineering and Physical Science Research Council and the BT Research and Innovation through the Industrial Cooperative Awards in Science and Technology Studentship.

ABSTRACT 5G definition and standardization projects are well underway, and governing characteristics and major challenges have been identified. A critical network element impacting the potential performance of 5G networks is the backhaul, which is expected to expand in length and breadth to cater to the exponential growth of small cells while offering high throughput in the order of gigabit per second and less than 1 ms latency with high resilience and energy efficiency. Such performance may only be possible with direct optical fiber connections that are often not available country-wide and are cumbersome and expensive to deploy. On the other hand, a prime 5G characteristic is diversity, which describes the radio access network, the backhaul, and also the types of user applications and devices. Thus, we propose a novel, distributed, self-optimized, end-to-end user-cell-backhaul association scheme that intelligently associates users with candidate cells based on corresponding dynamic radio and backhaul conditions while abiding by users' requirements. Radio cells broadcast multiple bias factors, each reflecting a dynamic performance indicator (DPI) of the end-to-end network performance such as capacity, latency, resilience, energy consumption, and so on. A given user would employ these factors to derive a user-centric cell ranking that motivates it to select the cell with radio and backhaul performance that conforms to the user requirements. Reinforcement learning is used at the radio cells to optimise the bias factors for each DPI in a way that maximise the system throughput while minimising the gap between the users' achievable and required end-to-end quality of experience (QoE). Preliminary results show considerable improvement in users' QoE and cumulative system throughput when compared with the state-of-the-art user-cell association schemes.

INDEX TERMS Backhaul, fronthaul, user-centric, user-cell association, SON, reinforcement learning, multiple attribute decision making.

I. INTRODUCTION

The targeted launch of 5G in 2020 promises to cater for the explosive increase in the number of connected devices and unquenchable users' thirst for higher throughput and lower latency. A key enabler to such monumental challenges, given the crowded microwave radio spectrum status, is the densification of small cells. Small cells are low power radio access nodes that may be deployed in parallel with high power nodes (macro-cells) for extra capacity or as a stand-alone coverage solution (e.g. indoor solution or remote hot-spot). Small cells reduce the necessary power for cells and user equipment (UE) to communicate owing to their close proximity, hence contribute to the green goals of 5G networks. Moreover, power reduction enables more frequent reuse of the spectrum within the same geographical area, thus, improves area spectral efficiency. The first backhaul challenge that arises from such a network deployment, however, is the need to connect all these small cells back to the core network, i.e., pervasive extensions in length and breadth of the existing transport network (referred to as backhaul).

On the other hand, features such as carrier aggregation, coordinated multipoint processing (CoMP), and cloud radio access network (C-RAN), in addition to the adoption of new radio spectrum bands such as millimetre wave, all result in higher radio bandwidth and/or throughput which demand higher bandwidth requirements on the backhaul links connecting the small cells. In addition, some of these features (e.g. CoMP and C-RAN) and some of the novel 5G user applications, such as tactile internet, require round trip delay over the backhaul to be less than 1 msec. Other services, such as e-health or security sensors, and stand-alone deployments of small cells, require ultra-high backhaul resilience (at least 99.999% up time) due to the urgency of the service or the fact that losing the backhaul connection leads to an absolute outage of the target area. Besides, 5G green incentives and increasing energy bills motivate the need for an energy efficient backhaul solution, hence adding more constraints to the already challenging problem.

Accordingly, 5G backhaul is a multi-constrained prime challenge that requires careful design to enable the delivery of the promised 5G performance. The challenge stems from the required extensions and the stringent performance requirements on the extended and existing transport links. Currently, the only solution that offers the required attributes is direct optical fibre; however, these are rarely available network wide, as fibre-to-the-cell, and deploying such a greenfield solution would require cumbersome trenching and laying fibre at an inhibitive and very costly scale. Accordingly, the industry is now looking at optimised ways of using the realistic backhaul while assessing the performance gap to prioritise the scheduling of backhaul improvements [1].

If we were to choose one characteristic to describe 5G networks, it would perhaps be diversity. The types of radio access cells, radio access technologies (RAT), backhaul solutions, and especially, devices and applications in 5G are more diverse than any other incumbent cellular generation. Eight 5G service use-case families have been identified, ''ranging from delay-sensitive video applications to ultra-low latency, from high-speed entertainment applications in a vehicle to mobility on demand for connected objects, and from best effort applications to reliable and ultra-reliable ones such as health and safety'' [2]. Moreover, these services will be delivered across a wide range of devices with different capabilities in caching, processing, signal amplification, MIMO, and battery-life.

According to the broad variety of users' requirements and network capabilities, a cell-centric backhaul may not be the optimum option for service provisioning. To this end, a novel User-centric backhaul is proposed in which users associate with cells that satisfy their service requirements from both RAN and backhaul sections of the network; possibly leading to different backhaul/fronthaul links to cater for users served by the same cell. The novel association scheme is based on virtual cell footprints that are tailored for each user according to his/her QoE requirements and the network availabilities and constraints. The potential gain that can be obtained from User-centric backhauling, exploiting the heterogeneous backhauling options, promises to reduce the performance gap between 5G backhaul network expectations and realistic backhaul solutions, while capitalising on the existing infrastructure.

The rest of the paper is organised as follows. We first provide a literature review on user-cell association schemes that are backhaul-aware or content-aware in Section II. In Section III we present our novel User-centric backhaul scheme supported by preliminary results and analysis. Section IV discusses advantages and related challenges to realising the proposed User-centric backhaul. Finally, in Section V we conclude the paper.

II. STATE-OF-THE-ART USER-CELL ASSOCIATION

Traditionally, user-cell association in both idle and active modes is based on the received signal strength at the mobile device level, for all cellular generations. In idle mode, the mobile measures all available downlink (DL) signals from the cells in the authorised network, and once it decodes the cell identification data, ranks the candidate cells based on the strength of the DL common channel. The mobile device attempts to access the identified potential serving cells, starting from the highest ranking cell, until one of them grants access. In active mode, the mobile device periodically measures the DL signal strength of the serving cell's neighbouring cells and reports it to the RAN, which uses the data to rank potential candidates for handover.

Such ranking and selection mechanisms are suited for networks designed to ensure one prime serving cell within a given coverage area, and where most mobile devices are operated by humans with similar quality of service (QoS) expectations. In the presence of heterogeneous networks (HetNets), composed of umbrella-type macro-cells overshadowing multi-RAT small cells, and diverse users' requirements, such a simplistic decision-making becomes obsolete and inefficient.

A. CELL SELECTION IN A HETEROGENEOUS NETWORK

Small cells have very low transmitted power compared to macro-cells; this would result in most users ranking the macro-cell highest, hence, missing out on the extra capacity provided by the small cell layer. Besides, often the path loss between users and small cells is less than that corresponding to macro-cells which signifies that the resulting signal to interference and noise ratio (SINR) provided by the small cell may be better than that of the macro-cell, despite the fact that the actual received signal from the macro-cell is higher (given that advanced inter-cell interference coordination, ICIC, is operational between the two layers). A workaround to this problem is the cell range extension (CRE) mechanism, whereby an offset or bias factor, often referred to as CREO, is broadcast by small cells to bias their ranking and attract users to selecting them [3]. Authors in [4] propose to use Q-learning, a reinforcement learning technique, for users to optimise user-centric bias values that would reduce the number of users in outage in the system. Guvenc in [5] analyses the capacity and fairness of HetNets with CRE when deployed with interference coordination between network layers, showing an improvement on both uplink and downlink. Authors in [6] propose a distributed solution to load balancing in a three-tier network, using optimised CRE values that reflect the load of the corresponding cell, showing more than three-fold gain in edge user throughput and two-fold in that of median users, compared to traditional user-cell association scheme. Q-learning is employed again in [7], as a self-optimised network (SON) technique, by cells (small and macro) to adjust dynamically their corresponding CRE offset values and the ICIC mechanism leading to improvement in users' throughput.

B. QUALITY-AWARE CELL SELECTION

CRE, as a stand-alone solution, addresses the selection between different network layers and may also be used for load balancing; however, it fails to build on the heterogeneity side of multi-RAT environment and user requirements. Authors in [8] formulate a user-cell association scheme guided by the users' desired throughput in a HetNet (with a unique RAT) and propose a centralised solution. They compare their proposed scheme to the traditional and to the fixed CRE approaches showing gains with the quality-aware scheme. In [9], a fuzzy logic call admission control scheme is proposed for a multi-class traffic cellular mobile network. Three types of calls are considered: voice, video, and data traffic, each with different QoS requirements, in a one-layer network. The admission control consists of giving call types with higher priority, such as voice, precedence over other new or existing data calls, for instance, when allocating a cell's resources for either handover or new call admission. Authors show an amelioration in handover success rate for critical call types while maintaining other calls with minimum probability of dropping. A QoS-aware load balancing algorithm for a joint group call admission control in HetNets is proposed, which admits mono-type calls to different networks depending on the corresponding loads in the candidate networks [10]. In a simulated example consisting of five overlapping networks (2xWLAN, 2xUMTS and 1xWiMAX), the authors show that the proposed algorithm reduces the call blocking rate when compared to schemes that either consider user satisfaction only or those that select the network with minimum load only, under a high number of simultaneous call requests. A novel call admission control algorithm is proposed in [11], in which various types of call requests with various QoS parameters are considered in a multi-RAT environment, with the objective of offering the required QoS to new calls without degrading the existing calls' quality. The mechanism consists of two stages. Fuzzy logic is employed in the first to select the best cell in each RAT (based on load and signal level), and fuzzy multiple attribute decision making is used in the second to select the best RAT based on the QoS requirements of the given user. The algorithm also gives higher priority to calls in handover over new calls and prioritises calls based on their respective QoS attributes. A user-centric joint call admission control scheme is proposed, in which RAT selection is based on user preference (e.g., cost, data rate, security, and battery consumption) in [12]. Handover calls are given priority over new calls while guaranteeing QoS requirements of admitted calls. The authors use fuzzy multiple-attribute decision-making technique in the RAT selection and propose a Markov model to evaluate the overall call blocking probability and handover call dropping probability.

C. STATE-OF-THE-ART BACKHAUL-AWARE CELL SELECTION

Mechanisms introduced in the previous section build on user QoS diversity and/or RAT diversity to optimise the user-cell association but ignore the backhaul conditions. However, the backhaul is the new bottleneck of next cellular generations, as opposed to the radio access which limits the performance of incumbent networks. Thus, call admission schemes that are blind to the backhaul status may effectively be shifting the problem from the radio to the backhaul; they are essentially neither solving the user QoS problem nor the network efficient utilisation problem of next generation networks. There has been recent research towards developing a backhaul-aware cell selection scheme with promising gains as described in the following paragraphs.

1) BACKHAUL-CAPACITY-AWARE

Knowing that next generation networks are likely to have a heterogeneous backhaul and building on the fact that traffic in HetNets fluctuates more frequently and with larger variance than mono-layered deployments, it is then instinctive to consider that various cells in the network would have different and variable backhaul capacity to offer to users. For instance, authors in [13] propose an algorithm for workload balancing among backhauls that occurs at the user-cell association phase and relies on the geometrical partitioning of the practical service area. Load control over the backhaul network is addressed in [14] through user-cell association that is aware of the radio conditions in addition to the backhaul available bandwidth. The problem is formulated as a multiple-choice multidimensional knapsack problem and users requesting service have various data rate expectations. Simulations demonstrate that the same system capacity is maintained with the proposed algorithm with fewer backhaul resources; in other words, the algorithm leads to better performance under backhaul bottleneck conditions. In [15], authors build on the previously introduced concept of downlink/uplink decoupling, such as in [16], by explicitly considering the available backhaul capacity during the association process in addition to the cell load. Another example of backhaul-capacity-aware cell association is our previous work, [17], in which the extended cell range of small cells is dynamically adjusted, using reinforcement learning, to balance the user-cell association based on the users' capacity demand and available joint backhaul and radio capacity. It is shown through simulations, that such an approach results in comparable system throughput to static cell range schemes while improving the QoE of 15% of users.

2) BACKHAUL-DELAY-AWARE

Heterogeneous backhaul networks consist of diverse types of transport links with dynamic latency depending on the technology type, topology, load etc. Besides, some new user applications have very low tolerance to end-to-end delay;

thus, delay-aware user association becomes critical and should account for the backhaul's impact on the latency perceived by users. Authors in [18] analyse the relative delay and reliability of wireless networks with fibre-optic-based backhaul, dependent on fibre cuts, topology, and faults. Accordingly, they propose a distributed user-cell association algorithm that is aware of the dynamically changing delay and reliability over the backhaul while balancing the load over the network. The scheme consists of various types of cells periodically updating information on their respective backhaul conditions and broadcasting raw values of delay and reliability. Consequently, users would try to initiate association requests to the most suitable cell by fist looking at the SINR level, and then by comparing their respective QoS requirements to the cells' advertised backhaul capabilities. Simulation results show that the proposed algorithm outperforms state of the art user association schemes in terms of reduction of delay and improvement in reliability.

A recent work by Zhang et al. proposes to use a backhaul-delay-aware user-cell association scheme, based on the CRE feature with optimised setting of CREO per network layer aiming to minimise the mean network packet delay [19]. Through their developed mean network packet delay model, they compare the proposed scheme with the traditional cell selection and backhaul-unaware CRE scheme. The mean network packet delay is better (or equal) to all other schemes when the optimum CREO is used on all network layers and the results are validated by simulations for different cell and gateway densities. A joint radio-backhaul delay objective is targeted in [20] in which authors consider a two-tier HetNet with wireless backhaul (out-of-band). The proposed algorithm relies on the CRE concept with a centrally optimised cell-specific bias factor to attract users to selecting cells with minimum end-to-end delay. Simulation results show consistent reduction in mean packet delay when compared to backhaul-unaware schemes.

A pioneering work on backhaul-aware resource management is offered in [21] where authors propose a novel distributed reinforcement learning mechanism which benefits users served by macro-cells to improve their performance by selecting suitable small cells for data coordination. The small cells connect back to the macro-cell using either in-band wireless or wired backhaul links with limited capacity. The utility function of the users is the ratio of resulting throughput over incurred delay. The work develops and investigates the gains of such a scheme over the uplink transmission direction and shows considerable improvement in average user utility.

3) BACKHAUL-ENERGY-AWARE

Reduction in energy consumption has become a focal goal in designing cellular networks, and the corresponding backhaul contribution is increasing with the widespread of small cells. Consequently, backhaul energy consumption needs to be considered in any energy optimisation exercise, such as backhaul-energy-aware user-cell association. For instance, authors in [22] propose such a scheme which reduces the number of active cells and backhaul switches to save on energy consumption. The results show a significant drop in used energy at the expense of a throughput degradation.

A context-aware and backhaul-energy-aware heuristic algorithm is proposed in [23], that first sorts candidate cells in descending order based on radio access energy efficiency, then selects those with minimum number of backhaul hops (i.e. less energy consumption), and last checks for available resources on the selected cells, moving to the next in list in case of shortage. Users with different throughput attributes are considered, thus, the algorithm is context-aware and biases the user-cell association based on the user's required throughput.

III. USER-CENTRIC BACKHAUL SCHEME

Backhaul-aware cell selection is a promising research direction for solving the holistic user-network association problem instead of shifting the bottleneck from radio to backhaul. The state-of-art work presented in Section II-C demonstrates the potential of such approaches, although none of the works fully capitalises on users QoS diversity. Besides, solutions proposed are mostly centralised and suffer from high complexity in general and lack of flexibility and ease of deployment. Our novel scheme, the User-centric backhaul, addresses these two shortcomings as explained in the following paragraphs.

A. BACKGROUND

Next generation cellular networks are heterogeneous in several ways. The types of cells range from macro-cells to femto-cells and include multi-RAT capabilities as well as remote radio heads, repeaters, and devices acting as relays. The RAN architecture may include traditional distributed RAN (D-RAN), C-RAN, and hybrid versions in between. The backhaul network is also heterogeneous since it employs diverse technologies such as copper-based, fibre-based, and wireless. And within each category, there are a plethora of options affected by distances and topologies as well as technology specific variants, such as VDSL and G.fast for copper-based links, direct fibre and xPON for fibre-based links, microwave or millimetre-wave, in-band or out-of-band for wireless connections, just to name a few. The users accessing the system are diverse as well in their respective devices' capabilities, applications' attributes, mobility, priority, and their preferences in ranking different network aspects such as cost, speed, reliability, etc. Moreover, the radio and/or backhaul network may be shared by more than one operator rendering its optimisation more challenging.

There are thus numerous candidate cells for users to connect to at any point and more options to backhaul to the core network. The network operators' prime objective remains the same, i.e. to maximise their revenue; hence, they want to maximise the users' QoE to increase their market share while minimising the network expenditure. Where in previous networks, the radio access was the main bottleneck and the network optimisation consisted majorly of reducing the number of cells and maximising their spectral efficiency; 5G comes with broader challenges and new opportunities. Optimising the network has become an end-to-end endeavour as opposed to one that focuses on the radio network part. An optimised network operation entails intelligent user-cell-backhaul associations that maximise the utilisation efficiency of the network in parallel with users' QoE as a first goal. When it is no more possible to maintain users' QoE with the given infrastructure, network expenditure should be considered in an optimised manner. Hence, the optimised network operation should highlight the areas that require least cost with highest pertinent gain to enable cost-effective and optimised network expenditure. The traditional association scheme that is based on radio signal strength is obsolete and needs to be replaced with a mechanism that captures the diversity of the problem and benefits from the heterogeneity of the network. Moreover, in view of the explosive spread of small cells which increases the complexity of the optimisation problem, and the need for fast adaptability to dynamic network conditions and users behaviour, it is essential to employ distributed SON techniques to manage this matching exercise.

B. SYSTEM MODEL

The novel scheme, User-centric backhaul, splits the optimisation problem into two parts: the routeing problem and the user-cell association problem. The routeing problem consists of dynamically adapting the routeing of data streams in the transport network based on load conditions or changes and network faults in both radio and transport networks. Moreover, routeing optimisation objectives are flexible, such as aiming to reduce the mean packet delay, or energy consumption, or achieving load balancing, etc. We propose to have an entity, the backhaul as a service (BHaaS), that interacts with the RANaaS[1] and overlooks this optimisation exercise which may be solved in a partly centralised and partly distributed manner. The link state information of all links in the backhaul network is dynamically updated, and cells (that are also transport nodes) use this information to periodically update the end-to-end DPI of their respective backhaul link(s). Indeed, a cell in 5G networks may have more than one option for backhauling for reliability, capacity, and diversity purposes; and its backhaul links may be using different technologies. In this paper, the focus is mostly on the second part of the optimisation problem.

In the second part, the cells use the updated DPI information related to their backhaul link(s) jointly with the dynamically changing radio conditions to optimise a set of bias (CREO) values that reflect different constraints/capabilities of the end-to-end network. A high capacity-based bias value indicates that the cell is capable of ensuring end-to-end high capacity to potential users, whereas a low latency-based bias value is associated with high end-to-end latency, thus, discouraging users with stringent delay requirements. Other bias values may correspond to the level of energy efficiency, reliability of the connection, cost per bit, relative security, etc. On the other hand, users have relative weights to different attributes affected by the device capabilities, the user preferences, and the application used. For instance, a remote smart metre may have high weight on energy efficiency, in view of the costly and difficult task of changing batteries, and very low weights on capacity and latency. An e-health sensor, however, would have high weights on reliability and latency instead. A corporate customer would prefer to access cells with the highest data speed, so will associate high weight on throughput attribute, where a student would prefer the cheapest and would associate high weight on cost, even if they are both using the same device and the same application. Consequently, each user will calculate his/her user-centric bias value with respect to each candidate cell, based on his defined weights and the cells' broadcast bias values. With diligent setting of these bias values, it is possible to optimise the matching exercise in a way that satisfies the users' QoE (based on users' needs and network availabilities) while respecting the network's dynamic status and objectives (updated periodically with link state information and radio conditions). This leads to a user-centric virtual perspective of the network cells' footprints, tailored to each user's needs.

The User-centric backhaul approach is thus an extension of the CRE scheme that jointly accounts for the radio and the backhaul conditions while creating tailored cell ranges for individual users based on their respective needs. The challenging part in solving the user-cell-backhaul association problem lies in solving the optimisation problem which grows in complexity with added attributes or bias values. In [17], a simplified version of the problem is simulated which considers a unique attribute reflecting the end-to-end network capacity. The results from [17] motivate solving the user-cell-backhaul association problem in a distributed manner, using SON techniques, such as Q-learning.

C. PROOF-OF-CONCEPT CASE STUDY

A case study is presented here to demonstrate the potential of the proposed User-centric backhaul scheme. The problem is formulated as follows:

- All users are assumed to have the same number of QoE indicators that matches the number of bias factors in all cells. This assumption does not undermine the heterogeneity of the system since different users allocate different weights to each QoE indicator. If a cell has more bias factors than a given user, a nil value may be associated with the weight of the user's undefined QoE(s). If a user has more QoE indicators than the number of bias factors broadcast by a given cell, a nil value may be associated with the missing bias factor(s).
- All cells have only **one** last-mile backhaul connection to the network. If more connections were considered between small cells and the first aggregation point, the routeing algorithm at the cell would become more complex. Moreover, each bias factor may reflect the

[1] Radio access network as a service. www.ict-ijoin.eu.

performance of a different connection which ranks best in capacity, latency, energy efficiency, etc. Nonetheless, the user-cell association that is solved with the proposed novel approach in unaltered, and is transparent to the number of last-mile links connecting the radio cells.

- The RAN architecture is uniform, i.e. C-RAN or D-RAN or hybrid solution is assumed in all cells in the network. The RAN architecture would certainly impact the generated load on the backhaul. This dependency may be captured in the method the link status information is interpreted in the capacity-based bias factor calculation. On the other hand, knowing that more centralised RAN architectures are less delay-tolerant, the incurred latency requirement may supercede the users' latency QoE. In brief, the RAN architecture would not impact the way the user-cell-backhaul association scheme is done thus would not undermine the validity of the User-centric backhaul scheme.

1) PROBLEM FORMULATION

The objective of the identified problem is to maximise the total system throughput while minimising the unsatisfactory performance perceived by served users. The proposed method consists of finding the setting(s) of bias values to each of the small cells in the network that would satisfy this objective. The difficulty in solving this problem is due to the permanently changing network conditions from both the radio access and the backhaul sides. The radio network conditions vary according to the users' movements, activities, and shadowing conditions, in the serving and interfering neighbouring cells. The backhaul network conditions vary due to fluctuating traffic load, faulty routers, link outages, etc.; these changes are reflected in the link status information that is received by the cells. It should be noted that traffic load variations are not necessarily caused by the cells in the system considered since parts of the transport network are often shared among various RATs and access points. We formulate the optimisation problem by starting with the definitions of the parameters as listed in Table 1.

The downlink received signal strength from cell C_c (the transmitter) to user U_u (the receiver), over the resource block K_k, can be expressed as follows:

$$J_{c,u,k} = \frac{\tau_c}{|\mathcal{U}_c|} \cdot H_{c,u,k} \tag{1}$$

$$H_{c,u,k} = \chi_c \cdot \delta_{c,u}^{-\alpha_c} \cdot \epsilon_{c,u,k} \tag{2}$$

where, τ_c is the total transmit power of cell C_c and $H_{c,u,k}$ is the channel gain between transmitter and receiver over the given sub-frame, as expressed in (2). A log-distance path loss is assumed with χ_c and α_c as the propagation constant and exponent, respectively, characteristic of cell C_c. $\delta_{c,u}$ is the Cartesian distance between cell C_c with coordinates (x_c, y_c) and user U_u (x_u, y_u), whereas, $\epsilon_{c,u,k}$ represents the composite fading component. Multi-path fading is averaged out since it varies faster than the response time of CREO adjustment; hence, $\epsilon_{c,u,k}$ is the log-normal shadowing component, assumed similar on all sub-channels assigned by cell C_c to user U_u within the resource block K_k. In current LTE systems, cell reselection decisions are triggered only if a given candidate cell ranks better than all others for a scenario-specific duration of time, relative to the RAT, user mobility, heterogeneity of network cells etc. The definition of the duration period is critical for filtering out the effect of fast (multi-path) fading and for avoiding the ping-pong effect, in addition to discouraging fast moving users from selecting the small cells, since these would necessitate another re-selection procedure soon after they have left the restricted coverage area of these cells. The same behaviour is desired in our scheme when users are ranking and selecting candidate cells; to this end, multi-path fading is averaged out and the received signal governing the selection decision is affected by the path loss and shadowing.

Each user in the system ranks the candidate cells (small cells and macro-cell sectors) according to the following equation:

$$R_{u,c} = \begin{Bmatrix} J_{c,u,k} + \sum_{q=1}^{|\mathcal{O}|} W_{u,q} \cdot V_{c,q}, \text{ if } C_c \in \mathcal{C} \\ J_{c,u,k}, \text{ otherwise} \end{Bmatrix} \tag{3}$$

where, $W_{u,q}$ and $V_{c,q}$ are the weight associated by user U_u to QoS Q_q and value of the corresponding bias factor broadcast by cell C_c, respectively, as detailed in Table 1. The cell that has the highest ranking with respect to user U_u, will be the allocated server given it has available resources; else, the next in the list will be tested for suitability until a serving cell is found or the user is declared out of coverage. If a serving cell C_c is found for user U_u, and a resource block K_k is allocated from $\mathcal{K}_c$, then the corresponding SINR, $\gamma_{u,c,k}$, can be expressed as follows:

$$\gamma_{c,u,k} = \frac{J_{c,u,k}}{\sigma^2 + \sum_{i=1,i\neq c}^{\mathcal{C}} \beta_{i,k} \cdot J_{i,u,k} + \sum_{m=1,m\neq c}^{\mathcal{M}} \beta_{m,k} \cdot J_{m,u,k}} \tag{4}$$

where, $\beta_{c,k} = 1$ if the resource K_k allocated to user U_u is used by cell C_c and 0 otherwise and where C_c could be a small cell or a macro-cell as detailed in Table 1. Hence, the corresponding SINR-based throughput of user U_u, served by cell C_c over the resource block K_k, can be computed as follows:

$$T_{c,u,k} = \text{BW} \cdot \log_2(1 + \gamma_{c,u,k}) \tag{5}$$

The required backhaul throughput, λ_c, is computed based on the cumulative captured radio throughput of users served by cell C_c, and the technology and network architecture dependent overhead, G_c.

$$\lambda_c = \sum_{u=1}^{|\mathcal{U}_c|} T_{c,u,k} \cdot G_c \tag{6}$$

The effective throughput per user is based on both the achieved SINR and the backhaul capacity of the corresponding cell. If the required backhaul throughput is larger

TABLE 1. Parameter definition.

- A set of macro-cell sectors, $\mathcal{M} = \{M_1, M_2, .., M_m, .., M_{|\mathcal{M}|}\}$, with Cartesian coordinates e.g., (x_m, y_m).
- A set of small cells, $\mathcal{C} = \{C_{|\mathcal{M}|+1}, C_{|\mathcal{M}|+2}, .., C_{|\mathcal{M}|+c}, ..., C_{|\mathcal{M}|+|\mathcal{C}|}\}$, with Cartesian coordinates e.g., (x_c, y_c).
- A set of CRE offsets (CREO), $\mathcal{O} = \{O_1, O_2, ..., O_o, ...O_{|\mathcal{O}|}\}$, where the value of CREO $O_o \in \mathcal{V} = \{0, 1, .., V_{\max}\}$ for all small cells $\in \mathcal{C}$.
- A vector of possible combinations of CREO settings per small cell, $\mathbf{s}_c = [V_{c,1}, V_{c,2}, .., V_{c,o}, ..., V_{c,|\mathcal{O}|}]$ such as $V_{c,o} \in \mathcal{V}\ \forall O_o \in \mathcal{O}, \forall C_c \in \mathcal{C}$.
- A matrix of possible CREO settings in the system:
$$\mathbf{S} = \begin{bmatrix} V_{|\mathcal{M}|+1,1} & V_{|\mathcal{M}|+1,2} & \cdots & V_{|\mathcal{M}|+1,|\mathcal{O}|} \\ V_{|\mathcal{M}|+2,1} & V_{|\mathcal{M}|+2,2} & \cdots & V_{|\mathcal{M}|+2,|\mathcal{O}|} \\ \vdots & \vdots & \ddots & \vdots \\ V_{|\mathcal{M}|+|\mathcal{C}|,1} & V_{|\mathcal{M}|+|\mathcal{C}|,2} & \cdots & V_{|\mathcal{M}|+|\mathcal{C}|,|\mathcal{O}|} \end{bmatrix}$$
- A set of backhaul solutions, $\mathcal{B} = \{B_1, B_2, ...B_b, ..., B_{|\mathcal{B}|}\}$, characterised by a set of attributes, $\mathcal{A} = \{A_1, A_2, ..., A_a, ..., A_{|\mathcal{A}|}\}$, where A_1 corresponds to the available backhaul throughput for all $B_b \in \mathcal{B}$. Each attribute A_a, of backhaul B_b in cell C_c may take any value, $P_{c,b,a}$, such that, $(P_{b,a})_{\min} \leq P_{c,b,a} \leq (P_{b,a})_{\max}$, where $(P_{b,a})_{\min}$ and $(P_{b,a})_{\max}$ are fixed values that depend on the backhaul technology, network topology, etc.
- A set of users, $\mathcal{U} = \{U_1, U_2, ..., U_u, ...U_{|\mathcal{U}|}\}$, with Cartesian coordinates e.g., (x_u, y_u).
- A subset of users served by cell (macro-cell sector or small cell) I_i, $U_i = \{\forall U_u \in \mathcal{U} \mid R_{u,i} > R_{u,j} \forall J_j \in (\mathcal{C} \cup \mathcal{M}) \mid j \neq i\}$, where $R_{u,i}$ is the rank given by user U_u to cell I_i (see (3)). Hence, the total number of users served by cell I_i is $|\mathcal{U}_i|$.
- A set of resource blocks shared between macro-cells and small cells, $\mathcal{K} = \{K_1, K_2, ..., K_k, ...K_{|\mathcal{K}|}\}$, where each resource block occupies a fixed bandwidth BW, e.g., BW= 12×180Khz.
- A set of resource blocks allocated by small cell C_c, $\mathcal{K}_c = \{K_{|\mathcal{K}|}, K_{|\mathcal{K}|-1}, .., K_k, ..., K_{|\mathcal{K}|-|\mathcal{U}_c|}\}$, or allocated by macro-cell sector M_m, $\mathcal{K}_m = \{K_1, K_2, ..., K_k, ...K_{|\mathcal{U}_m|}\}$. The transmit power of any cell C_c is shared equally among corresponding allocated resource blocks K_c.
- A function $\beta = \{\beta_{i,k} = 1$ if $K_k \in \mathcal{K}_i;\ \beta_{i,k} = 0$ otherwise, $\forall I_i \in (\mathcal{C} \cup \mathcal{M}),\ \forall K_k \in \mathcal{K}\}$
- A set of QoS user requirements, $\mathcal{Q}_u = \{Q_{u,1}, ...Q_{u,q}, ..., Q_{u,|\mathcal{O}|}\}\ \forall U_u \in \mathcal{U}$.
- A weight, $W_{u,q}$, is associated with each QoS requirement, $Q_{u,q}$, defined by each user U_u, reflecting the user's preferences, device's capabilities, and application's attributes, such that $0 \leq W_{u,q} \leq 1$, $\forall U_u \in \mathcal{U}, \forall Q_{u,q} \in \mathcal{Q}_u$
- A set of measured user QoS, $Q'_u = \{Q'_{u,1}, ...Q'_{u,q'}, ..., Q'_{u,|\mathcal{O}|}\}$, $\forall U_u \in \mathcal{U}$, which reflects the actual performance perceived by the user U_u.

than the available capacity of cell C_c ($P_{c,1}$ defined in Table 1), the effective user throughput is penalised as follows:

$$X = P_{c,1} - \lambda_c \tag{7}$$

$$T'_{c,u,k} = \left\{ \begin{array}{cc} T_{c,u,k}, & \text{if } X \geq 0 \\ T_{c,u,k} - \dfrac{X}{|\mathcal{U}_c|}, & \text{otherwise} \end{array} \right\} \tag{8}$$

2) CENTRALISED OPTIMISATION

The optimisation problem consists of maximising the total system throughput, given a set of constraints; it necessitates an overall vision of the network performance, hence, the usage of the term *centralised*. The problem can be formulated as follows:

$$\max_{\mathbf{S}}\ T(\mathbf{S}) \tag{9}$$

$$T(\mathbf{S}) = \sum_{c=1}^{|\mathcal{C}|+|\mathcal{M}|} T_c(\mathbf{s}_c) = \sum_{c=1}^{|\mathcal{C}|+|\mathcal{M}|} \sum_{u=1}^{|\mathcal{U}_c|} T'_{c,u,k} \tag{10}$$

subject to

$$\sum_{u=1}^{|\mathcal{U}_c|} \frac{Q'_{u,q} - Q_{u,q}}{Q_{u,q}} \leq \theta_q, \quad \forall Q_q \in \mathcal{Q}_u, \quad \forall c \in (\mathcal{C} \cup \mathcal{M}) \tag{11}$$

$$P_{c,1} - \lambda_c \geq 0, \quad \forall c \in (\mathcal{C} \cup \mathcal{M}) \tag{12}$$

where, $\mathbf{s}_c$ is the vector of CREO settings in cell C_c, θ_q corresponds to the optimisation target corresponding to QoS Q_q and reflects the accepted ratio of unsatisfactory quality.

3) DISTRIBUTED OPTIMISATION

The centralised optimisation problem increases in complexity with the increase in the number of cells, number of CREOs, number of possible CREO values, and number of backhaul links per cell, leading to a complexity of $\mathbb{O}(|\mathcal{V}| \cdot |\mathcal{O}| \cdot |\mathcal{C}|)$. To overcome this problem, we propose a distributed SON strategy in which each cell maximises its total throughput while respecting the identified constraints. The advantages of this approach are many-fold. Firstly, the complexity is reduced to $\mathbb{O}(|\mathcal{V}|\cdot|\mathcal{O}|)$, which is of pivotal importance in view of the exponential spread of ultra-dense small cell networks, hence the high cardinality of $\mathcal{C}$. Besides, such an approach is ideal for networks with fast dynamic changes, since it inherently adapts to added, deleted, or sleeping cells, modified spectrum allocation, changes to the backhaul network, etc. faster than a centralised optimisation mechanism which would require gathering up-to-date information from all relevant nodes to adjust the algorithm. A further relaxation of the optimisation problem stems from the consideration that the macro-cell backhaul link is ideal, hence infinite capacity, minimum latency, high security and resilience, etc. In other words, macro-cell backhaul limitations will not be the cause for breaching constraints (12) and (16). The distributed self-optimisation approach can thus be formulated as follows:

$$\max_{\mathbf{s}_c} \; T_c(\mathbf{s}_c), \quad \forall c \in \mathcal{C} \tag{13}$$

$$T_c(\mathbf{s}_c) = \sum_{u=1}^{|\mathcal{U}_c|} T'_{c,u,k} \tag{14}$$

subject to

$$\sum_{u=1}^{|\mathcal{U}_c|} \frac{Q'_{u,q} - Q_{u,q}}{Q_{u,q}} \leq \theta_q, \quad \forall Q_q \in \mathcal{Q}_u, \quad \forall c \in (\mathcal{C} \cup \mathcal{M}) \tag{15}$$

$$P_{c,1} - \lambda_c \geq 0, \quad \forall c \in (\mathcal{C}) \tag{16}$$

It should be noted that the User-centric backhaul scheme, in general, assumes that all macro-cells have fixed nil bias factor(s). Hence, users would only rank the macro-cell highest if the small cells together with their respective positive biases fail to provide a more attractive coverage. Thus, in essence, the macro-cell does not actively encourage users to select it and acts rather as a fallback solution.

4) SON REINFORCEMENT LEARNING

Machine learning is the prime application of SON functionalities which equip the network with the intelligence to observe relevant parameters and apply acquired experience in future actions. Reinforcement learning consists of enabling playing agents to learn optimum behaviour from interaction with their environment. An action is deemed optimum if it provides the best reinforcement signal. It is reached through a trial-and-error search which contributes to building an optimal map between the status of the agents and the action space. Accordingly, an agent would be able to identify the best action to take under varying conditions representative of its status. Reinforcement learning can be implemented in two basic ways: dynamic programming and Monte Carlo methods. The first requires accurate modelling of the environment, which is often not possible, whereas the second is not suitable for step-by-step incremental computation [24]. A third method is a combination of both, and is referred to as temporal difference learning; it does not require accurate modelling and has inherent incremental implementation capacity. Q-learning is such a reinforcement learning technique which uses a Markov decision process to link the status/action of an agent to a reward value. The objective is to identify the optimum policy that indicates the best action in any state of the agent that would maximise the reward.

In the context of distributed SON formulation of the User-centric backhaul approach, Q-learning may be adopted, as was done in [17]. In this scenario, the agents are the small cells, the actions are settings of the multiple CREO values, the state of the agents reflects its positioning with respect to the solution space of the optimisation problem, and the reward function is the objective function in (15). This may be formulated as shown in Table 2.

As Q-learning is based on Markov decision process, the given states should be independent, meaning that a small cell cannot be in two states at the same time. Although both states, $\Gamma = \{0, 1\}$, are based on users' throughput (when throughput-related QoE is considered), they remain independent because the first state relates to the SINR-based throughput (5), whereas the second is based on the effective throughput (8), given that θ is selected diligently in such a way that $\theta < (\frac{X}{|\mathcal{U}_c|}) \cdot \frac{1}{\min(Q_{u,1})}$, where $\min(Q_{u,1})$ is the minimum required throughput of all users in the system. From an implementation perspective, such a state confusion is never encountered since the cell is programmed to check for state 0 first; if the result is positive, no other states are considered.

Besides, from the Q-learning formulation described in Table 2, the first priority of each cell is to not exceed the backhaul capacity, depicted by the very high cost ($\Omega = 1000$) associated with this state. Next, the focus in on reducing the users' QoE to reach the target θ, ($\Omega = 100 \cdot \sum_{u=1}^{|\mathcal{U}_c|} \frac{Q'_{u,q} - Q_{u,q}}{Q_{u,q}}$). Once/if both these goals are reached, the last optimisation objective is to maximise the system throughput by encouraging each cell to reduce the gap between its available and carried backhaul capacities ($\Omega = 100 \cdot \frac{P_{c,1} - \lambda_c}{P_{c,1}}$). Such a formulation reinforces the user-centric aspect of the novel approach proposed as opposed to the network-centric goal of maximising the total system throughput without user QoE considerations.

5) PRELIMINARY RESULTS

As a proof of concept, a simplified model of the User-centric backhaul was simulated assuming two user attributes: throughput and latency. Link state information was randomly generated and periodically changed to reflect the backhaul status with respect to these two attributes. The system considered consists of one macro-cell with three sectors and 21 small cells in fixed locations; seven small cells overlaid by each of the macro-cell sectors. Small cells use Q-learning to self-learn two optimised bias values that indicate the joint radio and backhaul available throughput and latency, respectively. Each small cell is assumed to have only one backhaul link and macro-cells are assumed to aggregate the backhaul traffic of all small cells over an ideal backhaul. Users are randomly generated and uniformly distributed with higher

TABLE 2. Q-learning formulation.

Agents All small cells $C_c \in \mathcal{C}$,

State Any agent C_c may be in any of the three states below:

$$\Gamma_c = \left\{ \begin{array}{ll} 0, & if\ P_{c,1} - \lambda_c < 0 \\ 1, & if\ \sum_{u=1}^{|\mathcal{U}_c|} \frac{Q'_{u,q} - Q_{u,q}}{Q_{u,q}} > \theta_q, \forall Q_q \in \mathcal{Q}_u, \forall U_u \in \mathcal{U}_c \\ 2, & \text{otherwise} \end{array} \right\}$$

Action The actions of cell C_c (the agent) are the set of possible CREO settings, $\mathcal{S}_c$, represented by the vector $\mathbf{s}_c = [V_{c,1}, V_{c,2}, .., V_{c,o}, ..., V_{c,|\mathcal{O}|}]$,

Cost The cost estimated by cell C_c in state Γ_c when taking action $\mathbf{s}_c$ is computed as follows:

$$\Omega_{\Gamma_c,\mathbf{s}_c} = \left\{ \begin{array}{rl} 1000, & if\ \Gamma_c = 0 \\ 100 \cdot \sum_{u=1}^{|\mathcal{U}_c|} \frac{Q'_{u,q} - Q_{u,q}}{Q_{u,q}}, \forall Q_q \in \mathcal{Q}_u, \forall U_u \in \mathcal{U}_c & if\ \Gamma_c = 1 \\ 100 \cdot \frac{P_{c,1} - \lambda_c}{P_{c,1}}, & if\ \Gamma_c = 2 \end{array} \right\}$$

Q-table The Q-table will be updated according to the following, corresponding to agent C_c in state Γ_c taking action $\mathbf{s}_c$ with reward/cost $\Omega_{\Gamma_c,\mathbf{s}_c}$, where ϕ is the learning rate and η is the discount factor. $\Xi_{c,t}$ is the Q-table entry corresponding to state Γ_c and action $\mathbf{s}_c$ at time t, and $\Xi_{c,t'}$ is the updated entry.

$$\begin{aligned} \Xi_{c,t'}(\Gamma_c, \mathbf{s}_c) &= (1-\phi) \cdot \Xi_{c,t}(\Gamma_c, \mathbf{s}_c) \\ &+ \phi \left(\Omega_{\Gamma_c,\mathbf{s}_c} + \eta \cdot \min_{\mathbf{s}'_c} \Xi_{c,t}(\Gamma'_c, \mathbf{s}_c) \right) \end{aligned}$$

concentration in hot-spots (centred around the locations of small cells). QoE requirements and corresponding weights of users are also randomly generated.

The system is simulated over 50 runs; in each run the users are randomly re-distributed with the reassignment of QoE requirements and weights, and the link status information is regenerated randomly. In the proposed algorithm, we capture the variation of the network conditions through a Monte Carlo approach in which, within each of the 50 simulated runs, different snapshots of the system are considered in which the users' movements, activities, shadowing conditions, in the serving and interfering neighbouring cells are changed, resulting in realistic radio access network variations. In addition, the link status information of the connecting backhaul links is randomly varied to reflect changes in a realistic transport network. These simulation considerations are in-line with the work conducted in [17] and readers are encouraged to refer to this document for more details. The performance of the User-centric backhaul (User-centric-BH) is compared to three other scenarios, under identical network and users conditions, as follows:

- Backhaul-aware dynamic cell range extension [17] (BH-aware-CRE).
- SINR-based user-cell association (SINR-based).
- Cell range extension with fixed bias=6dB (Fixed-CREO).

The results of each scenario are collected over the 50 runs and the corresponding cumulative distribution function of each key performance indicator (KPI) is generated, as shown in Figures 1, 2, and 3. The first KPI shown in the left part of Figure 1 is the cumulative throughput of all served users in the system; that is the sum of all individual achievable throughput T as defined in (10). Clearly the CRE feature enhances the system throughput as seen by the noticeable improvement between the SINR-based approach and the CRE-based approaches (BH-aware-CRE, Fixed-CREO, and User-centric-BH). Besides, both backhaul-aware user-cell association schemes (User-centric-BH and BH-aware-CRE) reach comparable cumulative throughput to the Fixed-CREO, thus manage to maximise the system throughput. However, the BH-aware-CRE is seen to exceed the capacity of the User-centric-BH by ~0.6%. The second KPI shown in the right part of Figure 1 indicates the number of users out of coverage due to a shortage of radio resources, backhaul resources, or low SINR. The results conform with those in the left figure since the CRE-based schemes reduce the users out of coverage compared to the SINR-based method. The Fixed-CREO approach results in ~20% fewer users out of coverage compared to both BH-aware schemes because it ignores the backhaul constraints in the user-cell association. Nonetheless, since its corresponding cumulative throughput is comparable to the BH-aware schemes, it indicates that a large number of users are served with less than satisfactory throughput. Moreover, the BH-aware-CRE is also seen to reduce further the users out of coverage compared to the novel approach by ~3% which explains the corresponding small advantage in cumulative system throughput (left figure), however, at the cost of QoE degradation as will be demonstrated in the following figures.

Two other KPIs are considered as shown in Figure 2, which reflect the percentage of unsatisfied users with respect to throughput (y′) (left-most) and latency (z′) (right-most),

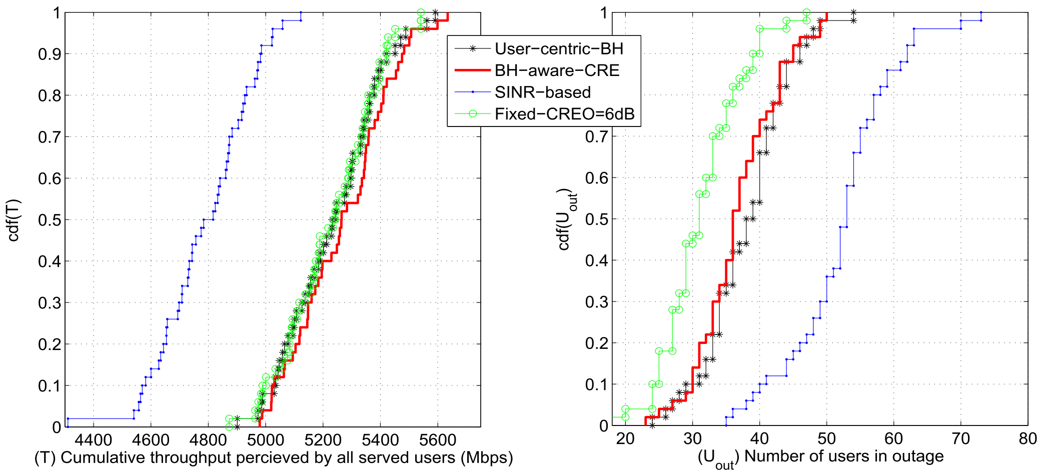

FIGURE 1. (Left) Cumulative users' throughput and (Right) Number of users in outage. CRE-based schemes outperform SINR-based and the novel User-centric-BH compares closely to the BH-aware-CRE in these performance indicators.

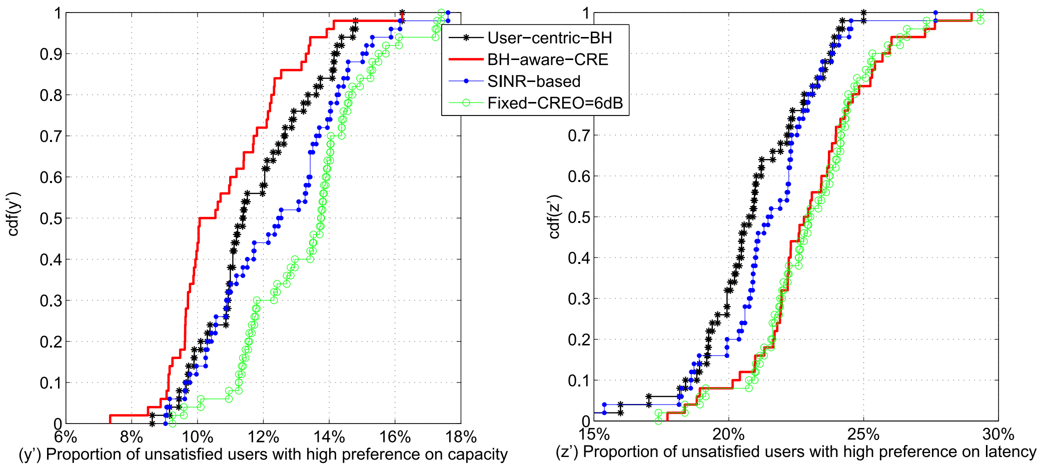

FIGURE 2. Percentage of unsatisfied users with respect to throughput, y', (Left) and latency, z', (Right). The novel User-centric-BH scheme compares to the BH-aware-CRE with respect to throughput QoS but results in major improvements with respect to latency related QoS.

computed as shown below:

$$y' = 100 \cdot \sum_{c=1}^{\mathcal{C}\cup\mathcal{M}} \sum_{u=1}^{|\mathcal{U}_c|} \frac{1}{|\mathcal{U}_c|}, \quad \forall U_u \in \mathcal{U} \mid Q'_{u,1} < Q_{u,1} \tag{17}$$

$$z' = 100 \cdot \sum_{c=1}^{\mathcal{C}\cup\mathcal{M}} \sum_{u=1}^{|\mathcal{U}_c|} \frac{1}{|\mathcal{U}_c|}, \quad \forall U_u \in \mathcal{U} \mid Q'_{u,2} > Q_{u,2} \tag{18}$$

The users taken into consideration in these results are those that associate high weight on throughput (left-most) or on latency (right-most), respectively. Both BH-aware schemes reduce the number of users with unsatisfactory throughput compared to the other scenarios, owing to their backhaul-capacity-aware user-cell association. Nonetheless, the BH-aware-CRE is seen to outperform the User-centric-BH in terms of reducing the number of unsatisfied users re-throughput by ~7.7%; this explains partially the corresponding reduction in users in outage noted in Figure 1 and will be justified in the next figure.

On the other hand, the novel approach clearly outperforms all the others in increasing the number of satisfied users re-latency, as seen in the right-most figure; ~10% amelioration is registered compared to the BH-aware-CRE scheme, emphasising the strength of the novel approach in delivering *user-centred* QoE.

Another set of KPIs is shown in Figure 3, which highlights the aggregate gap between the target and achieved QoE of users. The KPI Q_1 indicates the throughput and Q_2 the latency; y refers to the throughput shortage and z to the excess in latency as shown below. Note that users that are out of coverage are considered to have zero measured throughput and a latency of 1000msec.

$$y = 100 \cdot \sum_{c=1}^{\mathcal{C}\cup\mathcal{M}} \sum_{u=1}^{|\mathcal{U}_c|} \frac{Q'_{u,1} - Q_{u,1}}{Q_{u,1}}, \quad \forall U_u \in \mathcal{U} \mid Q'_{u,1} < Q_{u,1} \tag{19}$$

$$z = 100 \cdot \sum_{c=1}^{\mathcal{C}\cup\mathcal{M}} \sum_{u=1}^{|\mathcal{U}_c|} \frac{Q_{u,2} - Q'_{u,2}}{Q_{u,2}}, \quad \forall U_u \in \mathcal{U} \mid Q'_{u,2} > Q_{u,2} \tag{20}$$

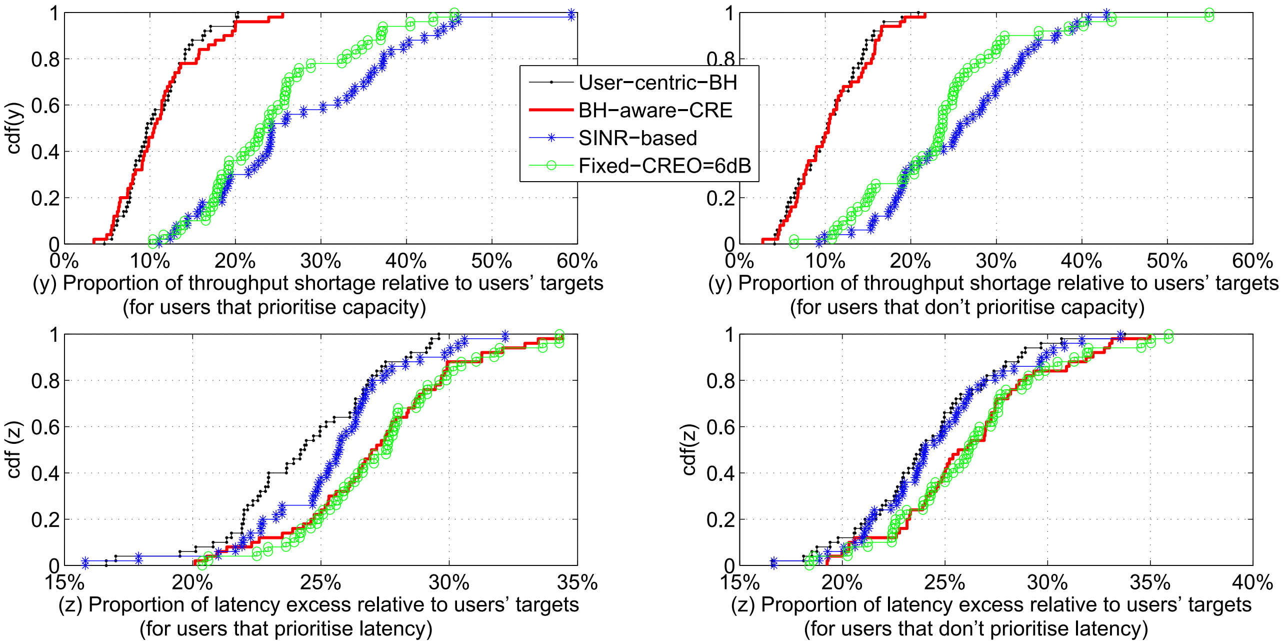

FIGURE 3. The upper figures show the shortage in achievable system throughput relative to the cumulative users' targets, looking at users that associate a high weight to throughput (upper-left) and those that do not (upper-right). The lower figures show the excess in achievable latency relative to the users' targets, looking at users that associate a high weight to latency performance (lower-left) and those that do not (lower-right).

The upper figures show the shortage in achievable system throughput relative to the cumulative users' targets, looking at users that associate a high weight to throughput (upper-left) and those that do not (upper-right). Both BH-aware schemes adjust the user-cell-backhaul association in such a way that maximises users' satisfaction with respect to throughput, as can be seen by the $\sim$55% reduction in throughput shortage compared to the Fixed-CREO scheme while achieving comparable cumulative system throughput, as shown in Figure 1. Moreover, the novel approach reduces the shortage in throughput slightly further than the BH-aware-CRE, despite the fact that more users are unsatisfied (see Figure 2). The User-centric-backhaul aims at reducing the throughput gap of the highest number of users and effectively manages to reach its objective while prioritising users with high weight on throughput; the BH-aware-CRE does not distinguish users' priorities as can be seen by comparing the left and right upper figures. These results clearly demonstrate the potential of the novel approach in efficiently allocating resources from the existing network. Looking at the performance of the backhaul-unaware schemes, the network is seen to have an average capacity shortage of $\sim$25%, whereas the novel approach shows only $\sim$10% shortage, thus saving the network operator considerable cost from redundant expenditures.

The lower figures show the excess in achievable latency relative to the users' targets, looking at users that associate a high weight to latency performance (lower-left) and those that do not (lower-right). These results advocate and promote further the advantage of the novel approach since it is the only method that maximises the users' latency-related QoE by $\sim$11% while satisfying the throughput-related QoE and achieving close-to-maximum cumulative throughput. Moreover, the User-centric-backhaul achieves better latency results for users with high weight on latency and better throughput results for those with high throughput weight, within the capabilities and constraints of the network.

6) ANALYSIS AND INSIGHTS

Assessing the effectiveness of an optimisation scheme may only be performed after identifying adequate and representative metrics. Authors in [25] highlight the critical role of user-centric QoE metrics in 5G, in addition to network-centric metrics. The results shown in Figures 1, 2 and 3 are averaged and summarised in Table 3 including four network-centric ($\overline{T}$, $\overline{U_{\text{out}}}$, $\overline{y'}$, and $\overline{z'}$) and four user-centric performance metrics ($\overline{y_{\text{high}}}$, $\overline{y_{\text{low}}}$, $\overline{z_{\text{high}}}$, and $\overline{z_{\text{low}}}$). The objective of the proposed optimisation problem is to maximise the overall system throughput while maximising the users' QoE. The overall system throughput is captured in T and, although the proposed User-centric backhaul scheme does not yield the best results among the four studied schemes, it lags by a mere 0.64% behind the best performing BH-aware scheme. The number of users out of coverage, U_{out}, is not an optimisation objective and the best results are reached with the Fixed-CREO scheme, which blindly takes users on the small cells layer irrelevant of the achievable users' QoE. Another measure of network performance is the number of unsatisfied users based on achievable throughput (y') and latency (z). From a network's perspective, the BH-aware-CRE scheme outperforms the novel scheme when it comes to reducing the number of unsatisfied users with respect to their achievable throughput. However, from a user-centric perspective, y_{high} and y_{low} are more relevant since

TABLE 3. Tabulated results from case study comparing the average metrics achieved by each of the tested schemes.

		User-centric-BH	BH-aware-CRE	SINR-based	Fixed-CREO	Best scheme
Cumulative throughput perceived by all served users (Mbps)	$\overline{T}$	5234.3	**5268.1**	4789.5	5226.4	BH-aware-CRE
Number of users in outage	$\overline{U_{\text{out}}}$	38.06	36.86	52.26	**31.26**	Fixed-CREO
Proportion of unsatisfied users with high preference on capacity (%)	$\overline{y}$	11.78	**10.87**	12.45	13.37	BH-aware-CRE
Proportion of unsatisfied users with high preference on latency (%)	$\overline{z}$	**20.90**	23.01	21.04	23.07	User-centric-BH
Proportion of throughput shortage relative to users targets (for users that prioritise capacity) (%)	$\overline{y_{\text{high}}}$	**9.73**	10.46	24.27	22.80	User-centric-BH
Proportion of throughput shortage relative to users targets (for users that do not prioritise capacity) (%)	$\overline{y_{\text{low}}}$	**10.23**	10.39	25.78	23.71	User-centric-BH
Proportion of latency excess relative to users targets (for users that prioritise latency) (%)	$\overline{z_{\text{high}}}$	**24.37**	27.17	25.74	27.60	User-centric-BH
Proportion of latency excess relative to users targets (for users that do not prioritise latency) (%)	$\overline{z_{\text{low}}}$	**23.78**	26.12	24.05	26.17	User-centric-BH

they measure the difference between the users target throughput and the achieved throughput for high weight and low weight throughput users, respectively. From the user-centric perspective, the novel User-centric backhaul approach outperforms all others, which indicates that although more users lag behind the target throughput, the gap is less important than in the case of BH-aware scheme. Effectively, a user whose achieved throughput is 90% of its target is more satisfied than a user who can receive 50% of his target, for instance. Although from a network perspective, these users count, exactly, in the same way, i.e., one additional unsatisfied user; from a user-centric perspective the former user is certainly more satisfied than the latter. The User-centric backhaul is centred around maximising the throughput QoE perceived by the users and indeed outperforms all other schemes. With respect to the latency QoE, z_{high} and z_{low}, the novel User-centric backhaul scheme outperforms all others since it is the only one that addresses this metric from both network and user perspectives.

Optimising 5G networks proves to be largely more complex that incumbent cellular generations due to the new user-centric dimension that is gaining a pivotal role in measuring the network's performance. The proposed novel scheme succeeds in sustaining network-centric metrics with a marginal degradation of 0.64% in total throughput while improving users' QoE on both targets: throughput (57%) and latency (11%). It will certainly be interesting to evaluate this scheme when more than two users' QoE indicators are targeted; however, one can deduce that with the User-centric backhaul scheme, at least, the same performance of the state-of-the-art schemes may be expected. Moreover, comparing the results from [17], which considered one QoE indicator, to the results of the case study with two QoE indicators, one can see that the user-centric metrics inarguably have improved, which gives us confidence that the User-centric backhaul scheme is capable of addressing 5G requirements better than the state-of-the-art schemes.

From a different angle, the results can be interpreted as a guide to required network upgrades. If the Fixed-CREO scheme is adopted, the network is deemed to lag behind the users' QoE throughput and latency targets by ∼23% and ∼27%, respectively. Such results would motivate a network operator to upgrade the existing backhaul network to accommodate the users' requirements. On the other hand, if the novel User-centric backhaul scheme were to be adopted, the network gap is reduced to ∼10% and ∼24%, thus reducing the required network extensions and highlighting the bottleneck which is latency in the given example. The insights drawn from the achievable metrics with the User-centric backhaul are critical for operators to plan the network optimisation manoeuvres and focus the spending on key network aspects that would unlock the users' perceived QoE. Such an approach distinguishes between two types of performance gaps: those that are due to resources mismanagement and those that cannot be circumvented by intelligent user-cell-backhaul association, hence reveals the hard limits of the network.

IV. CHALLENGES AND ADVANTAGES

Results presented and discussed in the previous section are very promising and motivate further development of the User-centric backhaul approach. There are, however, several challenges that need to be addressed prior to realising the full potential of the User-centric backhaul approach. Key challenges and advantages are identified and discussed in this section.

A. DYNAMIC AND ADAPTIVE ROUTEING

Two stages of optimisation are required to solve the User-centric backhaul scheme: the dynamic and adaptive routeing problem and the user-cell association problem. The BHaaS, with network-wide vision, addresses the first optimisation stage. It manages the optimisation targets of the backhaul nodes based on the network status (e.g. failure, constraints, etc.) and conditions such as load. Splitters and multiplexers are expected to adapt the ingress/egress capacity split in an SON-manner based on optimisation targets. Routers update link status information and routeing tables, in order to divert traffic according to optimisation targets and network status. The transport network is assumed to employ link status protocols (e.g. Open Shortest Path First (OPSF) and/or intermediate system-intermediate system (IS-IS)) for intra-autonomous system routeing. Traditionally, routeing metrics are manually assigned to each link in the network by operators, to bias routeing towards selected routes. The challenge thus relies on enabling dynamic routeing that is sensitive to the dynamic changes in the network and specific optimisation objectives.

There is an evident interest in the industry to develop dynamic routeing techniques, based on the available literature and state-of-the-art research. For instance, dynamic routeing using multi-path TCP[2] (MP-TCP), in a software defined backhaul network (SDN) is proposed in [26] showing considerable gains in flexible and adaptive routeing. Authors in [27] consider different link scheduling and dynamic routeing algorithms for load balancing and failure recovery in a millimetre-wave (mmWave) backhaul network, as part of the MiWaveS project.[3] SON is used in routers of a DiffServ-MPLS[4] mobile transport network to manage load balancing and resource allocation while preserving the quality of service [28]. Moreover, authors in [29] propose heuristic algorithms to manipulate routeing metrics centrally, by adopting dynamic, static, or vector-metric setting to find optimum values, following link status (capacity, load, availability). Self-optimised routeing is also investigated, using reinforcement learning, to adapt the routeing preferences for load balancing such as in [30].

On the other hand, there are various recent works that tackle adaptive backhaul resource allocation, such as [31] for xDSL technology, [32] for xPON, [33] for in-band mmWave, and [34] for active optical network. Authors in [31] propose a dynamic resource allocation scheme to maintaining the call quality through the resource constraint expedited forwarding queue of the digital subscriber line access multiplexers (DSLAMs). Whereas in [32] and [35], fibre-based dynamic multiplexing is used to distribute mobile fronthaul/backhaul capacity according to the changing radio traffic demand. Dynamic self-backhauling in a mmWave transport network is studied in [33], which requires that the routeing metric of a given link be dependent on other links' status (due to interference). An active remote node is proposed by SODALES[5] to improve backhaul/fronthaul usage efficiency and avail flexibility in provisioning backhaul capacity to heterogeneous endpoints such as residential femtocells, business pico-cells, macro-cells, and RRHs in [34].

In summary, dynamic and adaptive routeing is an essential optimisation target in the development of the User-centric backhaul approach. Nonetheless, it is also an aim of its own and has received recent attention from the research community as demonstrated. Hence, a key research direction is developing more holistic solutions of adaptive and dynamic routeing that are SDN-based and technology-agnostic, so they can operate over heterogeneous backhaul networks and deliver the required indicative link state information to the cells.

B. CELLS WITH MULTI-BACKHAUL OPTIONS

The User-centric backhaul scheme builds on the multi-options of backhauling cells to the core network. Such options stem primarily from the nature of the transport network, driven by the stringent resilience requirement, often realised through redundancy [29], [36], [37]. Besides, emerging networks are likely to witness higher cases of cells with more than one last-mile option of backhaul, resulting in larger sets of possible backhaul solutions. Based on the Small Cell Forum, coverage-motivated small cells require five nine's availability with low delay connectivity, similar to macro-cells [38]; such deployments may justify a last-mile backhaul topology that offers a 1+1 protection. Besides, a wireless mesh backhaul is a plausible solution forward, promoted by Nokia Networks in [39], for instance, which entails more than one option for backhauling from small cells to the network. Moreover, in-band backhauling or device-to-device (D2D) backhauling is an existing option for all operators, since it does not require additional expenditure on infrastructure or spectrum lease; hence, the possibility of using in-band last-mile may be considered as an alternative to the deployed backhaul link. In addition, point to multi-point wireless deployments, using microwave and/or mmWave, also result in multi-option-last-mile solutions, such as in [40].

Cells with multi-backhaul options represent another optimisation challenge and an eminent research direction. Each backhaul option would have different link state information; accordingly, the cell needs to account for these options in the way captured traffic is routed in a context-aware manner and in the way the aggregate effect of the multi-options is jointly analysed with the radio status and advertised to users. Moreover, this optimisation needs to be dynamic, adaptive, and responsive to changes in the network, hence motivating distributed SON solutions.

C. DYNAMIC AND ADAPTIVE USER-CELL ASSOCIATION

The User-centric backhaul scheme builds on user and network diversity in the user-cell association phase by guiding users, in idle or connected mode, to connect to cells able to offer their minimum required end-to-end QoE; while prioritising the usage of cells with better end-to-end QoE to users with such needs. To this end, each cell needs to first identify its end-to-end capabilities and constraints with respect to

[2] Transmission Control Protocol.

[3] Beyond 2020 Heterogeneous Wireless Networks with Millimeter-Wave Small Cell Access and Backhauling, supported by the European Union 7th Framework Programme.

[4] Differentiated Services- Multi-Protocol Label Switching.

[5] SOftware-Defined Access using Low-Energy Subsystems, http://www.fp7-sodales.eu/.

all possible attributes, such as throughput, latency, energy consumption, security, resilience, etc. Data corresponding to the backhaul network is available to cells, following the discussions in Sections IV-A and IV-B. Radio attributes are readily available to cells, as well, and are a result of interference levels, allocated resources, scheduling schemes, etc. In the example given in Section III, two radio attributes are considered, SINR levels and allocated resources, and two backhaul attributes, capacity and latency. These dynamic input parameters are used to define two joint bias values representing available end-to-end cell throughput and delay. More bias values can be envisaged to reflect the other possible user/network needs/constraints. The challenge, thus, is how to link the definition of these bias values to the raw input data available.

We propose to achieve this goal in an SON-based distributed approach, built on reinforcement Q-learning [17], as detailed in Section III-C3. Each cell is an agent that ''learns'' its set of optimised bias values by identifying the actions (setting of bias values) that minimise the cost function. Depending on the state of the agent the cost function is calculated differently. When the cell cumulative throughput exceeds the available capacity of the corresponding backhaul a high cost is associated. Next, the cell is in a state in which the objective is to reduce the gap between the desired and the actual user QoE of all captured users weighed by the user-specific QoE preferences, and the cost is calculated accordingly. Once this objective is reached, the cell is in the final state in which the aim is to maximise the load on the backhaul without breaching radio and/or backhaul constraints, and the cost is the percentage of unused backhaul capacity.

Q-learning delivers promising results when two bias values are considered, as in Section III, however, when more attributes and more options per attribute are considered the complexity of the problem increases further. For instance, if $|\mathcal{V}|$ possible settings of one bias value and $|\mathcal{O}|$ possible bias values (attributes) are considered, then the number of possible bias settings is $|\mathcal{V}|^{|\mathcal{O}|}$ which increases exponentially when $|\mathcal{V}|$ increases. Alternative reinforcement learning techniques may be more efficient in such a context, such as fuzzy logic or genetic algorithms, and need to be explored and analysed. The tradeoff between the added gain and increased complexity of the User-centric backhaul scheme with respect to increasing the number of attributes is, thus, another challenge and forms another research direction to solving the optimisation problem with minimum complexity.

Besides, the proposed User-centric backhaul SON scheme is assumed to continuously run on each cell to dynamically adjust to the changes in the network (overload, faults, alterations, etc.) and in users' behaviour (location, activity, priorities, etc.). It is anticipated that some QoE aspects, such as throughput, change at a faster rate than others, such as cost for instance. For this reason, we envisage that the tuning of CRE offsets related to the former QoE aspects should be more frequent than those related to the latter. On the other hand, the current distributed formulation presented in Section III, assumes independent multi-agent operation of reinforcement learning. However, inter-cell information, such as cell loads, is readily available today to all cells over the X2 interface and may be adopted in the learning process rendering cells as cooperative agents instead of independent [41]. Therefore, it is of pivotal importance to study the implementation possibilities of the User-centric backhaul scheme and evaluate their convergence and potential gains of adopting different learning rates per QoE aspect, and the advantages of cooperation among cells.

D. OTHER CHALLENGES

Although the results presented in Section III are promising as a proof-of-concept of the User-centric backhaul scheme; a comprehensive problem formulation and corresponding analytical modelling are still required to fully validate the concept. Thus, a key challenge is to capture the diverse performance aspects of the 5G heterogeneous transport network in an analytical model. Different research groups have addressed modelling of various backhaul performance indicators. For instance, the cost of the backhaul network has been modelled in view of the technology deployed and the network topology in different works, such as [42]–[44]. Authors in [44] propose analytical models to capture the delay of the backhaul network assuming it is wireless or heterogeneous (i.e., a combination of wired and wireless technologies), respectively. Authors in [19] model the delay in networks using heterogeneous backhaul solutions, composed of fibre links, xDSL, mmWave, and sub-6 GHz, and derive the mean packet delay over both the radio and backhaul networks. Given that energy consumption has leading importance in future networks, recent works have addressed modelling this backhaul aspect based on carried traffic and topology, such as [45] and [46]. Reliability and security of the backhaul are also critical and are captured in the proposed analytical model in [47]. This is certainly a key research direction that still requires development to represent fully the performance and constraints of different backhaul technologies, topologies, etc.

On the other hand, the user-centric scheme also assumes that the user equipment can dynamically adjust its QoE weights according to the device's capabilities, the application's attributes, and the user's preferences. This requires changes in the user equipment procedures and the interface with the radio access network, hence necessitates efforts from the standardisation community. A prime research direction consists of taking different inputs from the device, the application, and the user to derive these weights in an efficient manner with minimum complexity.

E. POTENTIALS AND ADVANTAGES OF USER-CENTRIC BACKHAUL

The proposed novel User-centric backhaul scheme exploits the diversity in the 5G network on three levels: the radio network, the backhaul network, and the user's requirements. From the simplified example shown, we demonstrate that such a scheme can enhance users' QoE without degrading the total system throughput, thus realising both goals of cellular operators: retaining and increasing customers (enhanced QoE) and increasing revenue (system throughput), within the given network infrastructure.

Alternatively, it is also possible to reach optimised user/cell distribution through intelligent handovers. In this case, user-cell association is conducted in a backhaul-unaware manner; once connected, the network will collect data from users and compare to network availabilities and decide on suitable handover to reach an optimised user-cell match. However, such an approach would generate a redundant signalling load on the network to manage the handovers, and would strain unnecessarily the devices' batteries. In contrast, the proposed scheme promises to achieve this match without the redundant need handovers, by performing the user-cell-backhaul association intelligently and knowledgeably, from the call initiation phase.

Besides, the proposed scheme is self-optimised and distributed, thus does not limit network expansions nor deployment speed; also, the decision making is fast and automated from the users' side while the final decision and control are left to the network. Moreover, the additional signalling information required for realising the User-centric backhaul scheme is minimal, consisting of a few (possibly less than 10) offset values broadcast per cell, and the possible settings of each of these offset values are also restricted (possibly less than five). Consequently, the additional overhead in terms of signalling and deployment is minimal and promotes this approach compared to the alternative centrally adjusted match through handovers.

Another advantage of the User-centric backhaul scheme is that it is backwards compatible. A user capable of computing a user-centric bias will benefit most by virtually tailoring cell ranges according to their capabilities and his needs, and will contribute to the optimisation goals of the network operator. Another user, with lower complexity, may use the cell-centric bias value as in use today in LTE-A networks, and a third user may ignore all bias values if the feature is not supported by the device. Vice-versa, if a mobile device has advanced capabilities, in terms of User-centric CRE weights, compared to the serving cell(s)/network, it would still operate without the feature using the SINR-based user-cell association or the unique CREO feature.

V. CONCLUSION

We have presented a novel concept of User-centric backhauling, which exploits the diversity of the radio and backhaul networks as well as that of the users QoE expectations. The concept is managed in two stages: the dynamic and adaptive routeing and the user-cell association. In this work, we elaborate on the user-cell association part and develop a scheme that builds on the cell range extension mechanism while taking into account the backhaul constraints and the users' diverse requirements. We provide a proof-of-concept through a case study simulating a simplified version of the User-centric backhaul and demonstrate that our approach improves the users QoE by 55% relative to throughput and 11% relative to latency while maintaining comparable total system throughput to the maximum throughput approach. More work is required to fully validate our novel scheme; critical challenges and research directions are identified and discussed while exposing the advantages of the distributed SON-based User-centric backhaul concept.

ACKNOWLEDGMENT

The views expressed here are those of the authors and do not necessarily reflect those of the affiliated organisations. The authors would also like to acknowledge the support of the University of Surrey 5GIC (http://www.surrey.ac.uk/5gic) members for this work.

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